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Nonlinear neighbor embedding for single image super-resolution via kernel mapping

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ABSTRACT

In this paper we propose a novel nonlinear neighbor embedding method for single image super-resolution (SR). Unlike previous works, the relationship between the local geometric structures of the two manifolds constructed by low-resolution (LR) and high-resolution (HR) patches are considered to be nonlinear in this paper. To achieve this goal, the original LR and HR patch features are mapped onto the underlying high-dimensional spaces respectively using two nonlinear mappings. Then the mapped features are projected by two jointly learnt linear matrices onto a unified feature subspace, where the conventional neighbor embedding is performed to reconstruct the target HR patches for the LR input. In addition, the kernel trick is applied to avoid the direct computation of nonlinear mapping functions, which facilitates the computation. The effectiveness of our approach is validated by experimental comparisons with several SR algorithms for the natural image super-resolution both quantitatively and qualitatively.

1. Introduction

High-resolution (HR) images are needed in many practical applications such as computer vision, medical image diagnosis, video surveillance and satellite imaging. However, in some cases, it is hard to obtain an image at a desired high-resolution level due to the limitations of imaging systems and imaging environments. The limited image resolution may restrict the performance of original systems, for example, causing a decline in the correct recognition rate with the low-resolution (LR) images as input. Thus, it is desired to reconstruct an HR image from one or more LR images using some specific methods.

A simple type of approaches to improve the image resolution is based upon interpolation, such as Bilinear and Bicubic interpolation. Though they are easy to perform, they cannot generate the desired high-frequency information in the reconstructed HR images, which tend to be blurry. Thus, another type of methods, called super-resolution (SR) image reconstruction, has become an active area of research in recent years [1–3]. SR is a technique that generates an HR image from multiple input LR images or a single LR image [4,5]. It utilizes the prior constraints of the image characteristics, such as the smoothness or the edge features, or uses the training set to learn some certain relationship between LR and HR images or patches to reconstruct the HR target image. Conventional SR approaches deal with multiple LR images of the same scene and estimate an HR image by fusing these LR images that are aligned with subpixel accuracy. These approaches can be divided into two kinds: frequency-domain methods [6] and spatial-domain methods [7,8]. As an ill-posed problem, SR reconstruction needs regularization operations to stabilize the solution. For spatial-domain methods, it is easy to add some specific prior knowledge into the reconstruction process as a regularization item, thus this kind of methods has attracted more attention [9,10].

Another category of SR approaches [11–13,1] has placed focus on the application of the training set, which normally consists of pairs of LR and HR images or patches. We

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can either directly use pairs of the corresponding LR and HR patches from the training set [14,15] or derive certain relationship between these LR and HR patches by some machine learning algorithm [16–18]. Thus this kind of SR methods is also called example-based or learning-based SR techniques. Instead of relying on an external training set, several recently proposed SR approaches [19,20] exploit the information of the input LR image itself to serve as the training set.

In [14] Freeman et al. employed pairs of LR and HR patches directly in a Markov network to perform image SR. It requires a large-scale training set and thus is computationally intensive. The neighbor embedding (NE) method proposed by Chang et al. [11] can overcome this disadvantage. It assumes that the two manifolds constructed by LR and HR patches (features) respectively have similar local structures. Therefore, an HR patch can be reconstructed by a linear combination of its neighbors. Using this strategy it needs a smaller training set and gets preferable HR results. Since then, some NE-related algorithms have been developed [21–23]. However, the manifold assumption is not always true for the SR problem because there are one-to-many mappings existing between the LR and HR images (patches). To overcome this limitation, Li et al. [16] proposed to project pairs of LR and HR patches from the original manifolds onto a common manifold and employed a manifold regularization so that the local geometry of this common manifold is more consistent with that of the HR manifold than the LR manifold is. It performs well on the face image SR reconstruction. To deal with the generic image SR, Gao et al. [17] proposed a coupled constraint, named as GPPs, to select proper patches from the training set for each test patch. Then the original LR and HR feature spaces spanned by GPPs are mapped by two projection matrices onto a unified feature subspace, where the reconstruction of the HR patches is performed.

The aforementioned approaches [16,17] either map the LR and HR patches onto a common manifold or map the LR and HR features onto a unified feature space. It is interesting to find that they both use two linear projection matrices as the mapping functions to achieve these goals. It implies that the projection process is assumed to be linear in their methods, which means that the local geometric structures of the LR and HR patch (feature) manifolds are linearly related. Moreover, the dimension of the projection feature space is smaller than that of the LR feature, which is similar to the dimension reduction and usually results in the loss of information. In this work, we ask, is it possible that the relationship of local geometric structures of the LR and HR manifolds is nonlinear? And how to reduce the influence of the dimension reduction induced by the projection?

In this paper, we have proven that the relationship of local geometric structures of the LR and HR manifolds is better described as nonlinear. We map the LR and HR patch features onto a unified space by our nonlinear approach and illustrate the distribution of distances between the mapped LR and HR patch features in this unified space in Fig. 1. We also give the distribution of distances between the mapped LR and HR features in the unified space obtained by the linear approach in [17] in Fig. 1. From Fig. 1, we can see that there are more features distributed in the small distance region (e.g. region 0.4–1.0) for our approach than those for the linear approach in [17], which means that each pair of the mapped LR and HR features are more close to each other by our nonlinear approach than by the linear approach. It suggests that the local geometric structures of the LR and HR manifolds are almost the same in the unified space after being mapped by our nonlinear approach and the relationship of local structures of the LR and HR manifolds is better described as nonlinear in the original space. Therefore, the NE-based SR achieves more excellent results in the unified space. The experimental results in Section 4 also verify that our nonlinear method can achieve more excellent SR outputs than the linear algorithms.

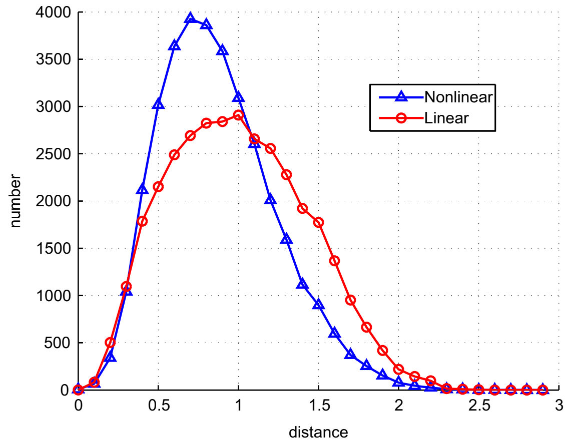

Fig. 1. Distributions of distances between the mapped HR and LR patch features in the unified space obtained by our nonlinear approach and the linear approach in [17] respectively. (Refer to the electronical version and zoom in for better comparison.)

In our approach, we first apply nonlinear mapping functions to map the LR and HR features onto the high-dimensional spaces. Then we project the high-dimensional features onto a unified feature space by two linear projection matrices. The manifold assumption is more satisfied in this unified feature space using our strategy. Therefore we perform the neighbor embedding reconstruction in this space. The results of the generic image SR reconstruction show the effectiveness of our method. Moreover, we use the kernel trick to avoid the direct computation of nonlinear mapping functions.

To the authors' knowledge, this paper is the first to apply the nonlinear mapping and kernel trick to the NE-related SR methods. The contributions of this paper are summarized below: (1) The local geometrical structures of the two manifolds of the LR and HR patches (features) are considered to have nonlinear relationship. (2) The nonlinear relationship of the local geometrical structures of the LR and HR manifolds in the original spaces is transformed into the linear relationship in the high-dimensional spaces with the help of the nonlinear mappings. In the high-dimensional spaces, the relationship of transformed features can be formulated as linear,